Productivity Dispersion and Input Prices: The Case of Electricity

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September 8, 2006

Abstract

Measured productivity differences among firms and establishments in the same narrowly defined industry are "extremely large" (Bartelsman and Doms, 2000). Empirical studies also find that more productive businesses tend to have higher market shares, low productivity businesses are more likely to exit and that market shares tend to rise over time for businesses with higher productivity levels and growth rates. These facts are intriguing, but their interpretation and analysis have been hampered by a dearth of data on output and input prices at the level of firms and establishments. As a result, most micro-level productivity measures are confounded by unmeasured demand variation and unmeasured input price differences.

In this study, we exploit a rich new database on Prices and Quantities of Electricity in Manufacturing (PQEM) to examine the relationship between physical efficiency in the use of electricity (output per kWh) and price paid per kWh, or "price efficiency". We also look at the impact of market structure on patterns of dispersion in electricity physical efficiency and prices.

Our results reveal large differences in electricity physical efficiency and prices within narrowly defined manufacturing industries. Given this substantial dispersion, we seek to explain how plants seemingly competing in the same market can exhibit such large dispersion in electricity physical efficiency and prices. We show there is a positive tradeoff within industries between the price and physical efficiency of electricity and that this tradeoff is more pronounced in electricity intensive industries. Finally, we find that plants producing in the same industry may not, in fact, be competing in the same market. We find evidence that an increase in local market density for locally traded goods yields a reduction in the dispersion of electricity productivity and physical efficiency.

1. Introduction

Measured productivity differences among firms and establishments in the same narrowly defined industry are "extremely large" (Bartelsman and Doms, 2000). Syverson (2004b) finds the interquartile range for log total factor productivity is around 30 log points and for log labor productivity is around 65 log points within 4-digit SIC industries in the U.S. This dispersion in measured total factor productivity and labor productivity may reflect many factors. For one, standard measures of plant-level productivity confound output price, input price and physical productivity since plant-level prices of outputs and inputs are typically not observed. Foster et al. (2005) investigate these issues for seemingly homogeneous 7-digit product classes in the U.S. with available physical output measures. They find substantial dispersion within narrow product classes in both measures of physical output efficiency and plant-level prices.[1] The latter paper also finds that plant-level price and physical output efficiency are inversely related (consistent with plants' facing downward sloping demand curves) and that these effects have distinctly different impacts on the survival of plants and the evolution of plant-level behavior.

In this paper, we explore the role of physical efficiency and price dispersion in a new and unique direction by taking advantage of a rich new database that permits measuring both physical units of purchased electricity and plant-level prices paid for electricity.[2] In earlier work (see Davis et al. (2006a)), we find there is tremendous dispersion across plants in the electricity prices they face and that the structure of this

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[1] Physical output efficiency, measured as physical output per unit input, has a within product standard deviation of 22 log points and output prices have a within product standard deviation of 18 log points.
[2] Foster et al. (2005) exploit data with measures of physical output and output prices but do not explore the role of dispersion in physical efficiency or price dispersion on the input side.

dispersion has changed markedly over time. While this earlier paper investigates the sources of electricity price dispersion in terms of quantity discounts and location effects, we do not explore the connection between electricity price dispersion and physical efficiency in the use of electricity. Given the findings on output price dispersion and physical output efficiency, it is naturally also of interest to explore the role of dispersion coming from the input side.

Earlier findings of substantial dispersion in revenue and physical based measures of productivity as well as plant-level output and input prices raise a variety of questions. There must be some form of friction, broadly defined, underlying this dispersion. This friction may reflect product differentiation even in narrowly defined sectors. As Syverson (2004a) emphasizes, the product differentiation in the concrete industry likely reflects differences in market structure across local areas since concrete is a homogeneous physical product that is typically shipped only short distances. He finds that dispersion in both total factor productivity and labor productivity is lower in local areas with more intense competition across plants.

In a related manner, the recent literature on firm dynamics also emphasizes that frictions may reflect a variety of adjustment costs for factors such as capital and labor, adjustment costs for adopting new technologies, and potentially related entry and exit frictions. The recent evidence from firm- and plant-level data provide support for the presence of these adjustment frictions, showing lower price and productivity plants are more likely to exit than higher price and productivity plants, which have higher market shares and are more likely to grow. Put more generally, in market economies like the U.S., while not all output is instantaneously allocated to the most productive unit as it

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would be in a frictionless environment, there is evidence of both static and dynamic allocative efficiency.

Our motivation for quantifying and studying the extent and connection between plant-level electricity price dispersion and physical efficiency (measured as output per physical unit of purchased electricity) is closely related to these questions of allocative efficiency. We seek to address the following basic questions. First, what is the extent of dispersion in electricity physical efficiency and electricity prices across U.S. manufacturing plants? Second, is there a tradeoff exhibited across plants within industries in terms of physical efficiency and prices – e.g., is it the case that plants in a given industry that face especially high electricity prices must have greater physical efficiency in order to compete in the same market? Third, how does market structure impact the patterns of dispersion in electricity physical efficiency and electricity prices?

To explore the third question, we build upon the hypotheses and findings of Syverson (2004a, 2004b). In these papers, Syverson explores the hypothesis that for locally traded goods, the intensity of local market competition will impact the dispersion of output prices and total factor productivity. The basic hypothesis is that in local markets for local goods, greater competition (as measured by market density) will yield lower price and productivity dispersion as high price, low productivity producers will not be able to survive in denser markets. Syverson finds evidence in support of this hypothesis for total factor productivity and output prices. We explore whether this hypothesis also holds for electricity physical efficiency and electricity prices.

The paper proceeds as follows. Section 2 describes the data and measures used in the analysis. Section 3 presents basic facts about the patterns of dispersion in electricity

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productivity and prices. In Section 4, we explore the tradeoff between electricity physical efficiency and prices within narrow industries. Section 5 examines the relationship of electricity intensity and the price-productivity tradeoff. Section 6 presents an analysis of the impact of competition on the dispersion of electricity physical efficiency and prices. Concluding remarks are in Section 7.

2. Data and Measures

2.1 Data Sources and Analysis Samples

To measure plant-level inputs and outputs, we rely on a new database called Prices and Quantities of Electricity in Manufacturing (PQEM). The PQEM contains roughly 50,000 plant-level observations in 1963, 1967 and each year from 1972 to 2000. Variables in the PQEM include expenditures for purchased electricity during the calendar year, quantity of purchased electricity (watt-hours), employment, labor costs, materials costs, shipments, and detailed information about industry and location. We constructed the PQEM mainly from the U.S. Census Bureau's Annual Survey of Manufactures (ASM) and various files produced by the U.S. Energy Information Administration.[3] The ASM is a series of nationally representative, five-year panels refreshed by births as a panel ages. Sampled plants account for about one-sixth of all manufacturing plants and three-quarters of manufacturing employment. Our analysis makes use of ASM sample weights, so that our results are nationally representative.

We exclude certain PQEM observations in forming our analysis samples. First, we delete plants with part-year operations or highly seasonal patterns of production,

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[3] We identified and resolved several issues with ASM data on electricity prices and quantities in the course of constructing the PQEM. We also checked ASM data on electricity prices and quantities against data from the Manufacturing Energy Consumption Survey, another plant-level source that relies on a different survey. See Davis et al. (2006b) for details.

because they typically face special tariff schedules with higher charges. In particular, we drop a plant-year observation when its number of production workers in any single quarter is less than five percent of its average number of production workers during the year. This restriction reduces the sample size by 1.7 percent. Second, we drop plant-year observations for which value added is non-positive. We measure value added as the value of shipments plus changes in finished goods and work-in-progress inventories less costs for parts and materials, resales, contract work, electricity and fuels. [4] We also drop all observations in an industry-year, if plants with non-positive value added account for more than five percent of shipments by the industry, i.e., the four-digit SIC code. These two restrictions reduce the sample size by a further 6.8 percent. Finally, to focus on plant-level variation within narrowly defined industries, we omit industry categories styled as "miscellaneous" or "not elsewhere classified." This last requirement cuts the sample size by 9.8 percent of the remaining observations. The resulting primary analysis sample has nearly 1.5 million plant-level observations, ranging from 34 to 68 thousand per year. [5]

We create a second analysis sample limited to plants that produce homogeneous products. Following Foster et al. (2005), we consider seven homogeneous products: corrugated and solid fiber boxes, hardwood plywood, ice, motor gasoline, ready-mixed concrete, roasted coffee, and white-pan bread. [6] Foster et al. develop a list of plants that

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[4] We deflate value added to 1987 $ using the NBER-CES Manufacturing Industry Database price indices for shipments, energy, and materials. Data and information for the NBER-CES Manufacturing Industry Database can be found at http://www.nber.org/nberces/nbprod96.htm.
[5] We adjust the original ASM sample weights to account for dropped observations, following the methodology of Hough and Cole (2004). A detailed description of the weight adjustment methodology is available on request from the authors.
[6] See Foster et al. (2005) for a detailed definition of each homogenous product. Unlike Foster et al., we combine block ice and processed ice into a single product category.

produce these homogeneous products in the Census years 1977, 1982, 1987, 1992 and 1997.[7] Our homogeneous products sample includes all observations for the plants identified by Foster et al., provided that the observation appears in the primary analysis sample and has an industry code consistent with the Foster et al. product classification. Our resulting homogeneous products sample contains about 48 thousand plant-level observations. We use this sample to gauge whether results for our primary sample are driven by product heterogeneity and quality differences within four-digit industries.

2.2 Productivity and Price Measures

We define electricity productivity at plant e in year t as

$$\varphi_{et} = \frac{VA_{et}}{EE_{et}} = \frac{VA_{et}}{P_{et}KW_{et}}, \tag{1}$$

where VA is value added, EE is expenditures for purchased electricity, P is price per unit of electricity and KW is the number of units. Taking logs, we decompose electricity productivity into two pieces, one that captures physical efficiency in the use of electricity and a second that reflects "price efficiency":

$$\log(\varphi_{et}) = \log\left(\frac{VA_{et}}{EE_{et}}\right) = \log\left(\frac{VA_{et}}{KW_{et}}\right) - \log(P_{et}) \equiv \gamma_{et} - p_{et}. \tag{2}$$

We interpret (the negative of) p as a measure of price efficiency, because a firm makes deliberate choices regarding location, scale, equipment voltage, load factor and responsiveness to peak-load pricing incentives that affect its average price per kWh. In Davis et al. (2006a), we show that most of the plant-level variation in price per kWh is explained by the plant's location and its annual purchase quantity. We also provide

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[7] Foster et al. (2005) require that the product of interest account for at least 50 percent of a plant's revenue in order to classify that plant as a producer of one of their homogeneous products. See Foster et al. (2005) for a more detailed description of their methodology.

evidence that price differentials on these dimensions reflect differences in customer supply costs for utilities. Thus, our earlier work provides a strong rationale for interpreting price per kWh as one aspect of the efficiency with which manufacturers make use of electrical power. We provide evidence below that plants face a tradeoff between physical efficiency in the use of electricity and price efficiency.

3. Dispersion in Electricity Productivity and Electricity Price

Table 1 summarizes the distribution of electricity productivity, physical efficiency and price efficiency within narrowly defined manufacturing industries. The clear message is one of tremendous dispersion in these measures among plants in the same four-digit industry. In the primary analysis sample, the intra-industry standard deviation of output per unit of electricity (physical efficiency) is about 90 log points, and the 90-10 differential is about 200 log points. By way of comparison, the intra-industry standard deviation of labor productivity is about 70 log points, and the 90-10 differential is about 140 log points.[8] These results are similar to those found in Syverson (2004b) for labor productivity.

The homogeneous products sample exhibits similar dispersion of physical efficiency within even narrower product categories. As seen in Table 2, there is considerable dispersion in output per unit of electricity in all seven homogeneous product categories. The evidence in Table 2 indicates that high productivity dispersion in the primary analysis sample is not simply an artifact of product heterogeneity within industries.

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[8] We calculate plant-level labor productivity as real value added divided by total hours worked. However, the ASM, and hence the PQEM database, only includes data on production worker hours so we must estimate total worker hours. We use a simple estimation method: total workers hours equals production workers hours times the ratio of total salaries and wages to production worker wages.

The dispersion in electricity prices paid by manufacturing plants is also large. In the primary analysis sample, the intra-industry standard deviation of price per kWh is about 35 log points, and the 90-10 differential is about 85 log points. Table 2 shows considerable price dispersion in all seven narrow product categories. These results constitute a dramatic violation of the law of one price, and they suggest that unmeasured input price variation is an important source of error in standard plant-level productivity measures. While Tables 1 and 2 consider price of electricity inputs only, casual empiricism suggests that quantity discounts and other sources of price differences are prevalent for many intermediate inputs including office supplies, computer software, legal services, information goods and airline travel.

In the analysis below, we study the relationship between electricity price and productivity, the effects of electricity's cost share on the price-productivity tradeoff, and the impact of product market competition on the intra-industry dispersion of physical productivity and electricity prices. The economic forces identified by our empirical work are likely to operate for other inputs as well.

4. Price and Physical Productivity in the Cross Section

Consider the relationship between a plant's physical efficiency in the use of electricity and its price per kWh. There are two competing hypotheses regarding this relationship. The first hypothesis maintains that physical efficiency and price efficiency are positively correlated in the cross section; in other words, plants with greater physical efficiency tend to pay less per kWh. This hypothesis follows from the notion that general managerial quality varies among plants, so that plants with better managers achieve higher efficiency in terms of both output per kWh and price paid per kWh.

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The second hypothesis maintains that the two aspects of electricity efficiency are negatively correlated in the cross section. One motivation for this hypothesis follows from cost minimization – plants that face higher electricity tariffs have stronger cost incentives to purchase electricity-saving equipment and to modify the production process in other ways that economize on electricity usage. Another motivation follows from market selection pressures. Plants with low efficiency in both respects have relatively high costs and, thus, are less likely to survive and grow. As a result, they are systematically selected out of the distribution of surviving producers.

There is probably a role for each of these economic forces in the cross-sectional relation between physical efficiency and price efficiency, but we do not seek to separately identify them here. Instead, our goal is to determine the prevailing cross-sectional relation between physical efficiency and price efficiency among plants in the same industry. That is, we investigate whether the first or second hypothesis provides a better characterization of the data. We also investigate, in the next section, how the plant-level relationship between physical efficiency and price efficiency varies with the importance of electricity in the production process.

To evaluate the two hypotheses, we pool the plant-level data over years, compute deviations of the plant-level efficiency measures about their respective industry-year means, and run regressions of the form:

$$\tilde{\gamma}_{ei} = \beta_i \ \tilde{p}_{ei} + \varepsilon_{ei}, \tag{3}$$

where e indexes establishments, i indexes industry (four-digit SIC), and a tilde indicates a plant-level deviation about an industry-year mean. The left side of (3) is the natural log of value added per kWh for plant e in industry i deviated about its mean value for plants

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in the same industry and year. The $\tilde{p}_{ei}$ term on the right side of (3) is the log price per

kWh for plant e in industry i deviated about the log price for plants in the same industry

and year. We fit (3) on our primary analysis sample, pooled over years. The key

parameters of interest are the β_i coefficients, which quantify the intra-industry

relationship between price and physical efficiency.

In estimating the regressions (3), we break the sample into distinct epochs that

pertain to four different periods in the evolution of real electricity prices. See Figure 1.

The first epoch runs from 1963 to 1973 and covers the latter part of a many-decades-long

decline in real electricity prices. The second and third epochs cover the years from 1974

to 1978 and 1979 to 1984, respectively. The oil price shock of 1973-74 and a less

favorable regulatory climate for the industry in the 1970s led to a reversal in the earlier

pattern of declining real prices.[9] Indeed, the real price per kWh for electricity purchases

by U.S. manufacturers roughly doubles from 1973 to 1984. We break this period of

rising prices into two pieces to allow for a surprise element in the shift from falling to

rising prices and a gradual adjustment to the changed outlook for electricity prices. The

fourth epoch, which covers the years from 1985 to 2000, is characterized by a resumption

of the secular decline in real electricity prices.

Table 3 summarizes our results from estimating (3) by industry for each of the

four epochs. The evidence very strongly favors the second hypothesis – namely, that cost

minimization incentives and market selection pressures generate a positive cross-

sectional relation between physical productivity in the use of electricity and its price per

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[9] See Section 2 of Davis et al. (2006a) for an overview of these regulatory developments and references to more detailed treatments.

kWh. According to the least squares estimation results in panel A, the β coefficients are negative in only 1 or 2 percent of industries. They are positive and statistically significant at the 5 percent level in more than 90 percent of the industries in all four time periods. The mean elasticity of physical productivity with respect to price ranges from 0.62 to 0.98, depending on time period. Elasticities in this range imply a very strong substitution response that ameliorates most of the cost increase induced by higher electricity prices.

A concern about least squares estimation of (3) is the potential for measurement error to bias the estimated β coefficients. Recall that the PQEM measure of price per kWh on the right side of (3) is constructed as the ratio of annual expenditures on purchased electricity to annual quantity of purchased electricity. Noise in the annual expenditures measure creates an attenuation bias that causes least squares estimation of (3) to understate the tradeoff between physical productivity and price. In contrast, because it appears in the denominator on both sides of (3), errors in the purchase quantity measure cause least squares estimation to overstate the price-productivity tradeoff.

To address these sources of bias, we exploit the fact that location accounts for a high percentage of electricity price differences among manufacturing plants. In particular, Davis et al. (2006a, Table 2) report that county fixed effects account for 31 to 67 percent, depending on year, of the between-plant variance in the log of electricity prices. This result implies that the plant's county is a good instrument for its price per kWh. For numerical reasons, we reduce the dimension of the instrument vector to one by first running cross-sectional regressions of log price on county fixed effects. The

predicted value of log price in this regression then serves as an instrument for $\tilde{p}$ in (3). To capture only industries for which county acts as a reasonable instrument, we restrict the instrumental variables estimation to industries with first-stage R-square values greater than 0.20.[10]

Panel B of Table 3 shows the results of the instrumental variables estimation of (3). While there are fewer positive estimated β coefficients in the instrumental variables estimation than in the least squares estimation, a majority of estimated β coefficients are still positive in every time period. Less than four percent of the estimated β coefficients are negative and statistically significant. The mean elasticity of physical efficiency with respect to price is notably lower for the instrumental variables estimation, ranging from 0.56 to 0.74, depending on time period. Panel C shows least squares estimation results for the same set of industries used in the instrumental variables estimation and, when compared to panel B, provides definitive evidence that the instrumental variables estimation produces lower mean elasticities than the least squares estimation. While we still see a strong substitution response to higher electricity prices, it appears that the least squares estimation of (3) overstates the true strength of that response.

5. Electricity Intensity and the Price-Productivity Tradeoff

The results in Table 3 strongly support the hypothesis of a tradeoff between price per kWh and physical productivity in the cross section of manufacturing plants. We identified two economic forces that produce this tradeoff – cost minimization and market selection. Economic theory suggests that these forces bite harder when electricity is a

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[10] We also estimated the instrumental variables specification with first-stage R-square cutoffs of 0.10 and 0.15, obtaining very similar results for these specifications.

more important factor input and a bigger share of costs. That is, the bigger electricity's cost share, the greater the incentive to adopt electricity-conserving production methods, and the greater the force of market selection on electricity productivity (physical efficiency and price).

This line of reasoning yields a third hypothesis: the plant-level tradeoff between price per kWh and physical productivity strengthens as electricity's cost share rises. To test this hypothesis, we consider industry-level regressions of the form:

$$\hat{\beta}_i = a + b\kappa_i + u_i, \tag{4}$$

where $\hat{\beta}_i$ is the estimated elasticity of physical productivity with respect to price for industry i, and κ_i is electricity's cost share in industry i. We measure the industry cost share by electricity expenditures as a fraction of industry value added, averaged over years within one of the four time periods defined above.

Figure 2 implements (4) and tests the null hypothesis that $b = 0$ using the least squares estimates for β. Each data point in the figure corresponds to a four-digit industry in one of the four time periods. As seen in Figure 2, the data strongly support rejection of $b = 0$, providing strong support for the hypothesis that a higher cost share for electricity leads to a stronger tradeoff between physical productivity in the use of electricity and the price paid by kWh. The effect is powerful and tightly estimated. For example, a five percentage point increase in electricity costs as a share of value added at the industry level raises the plant-level elasticity of physical productivity with respect to price by 16 log points.

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Figure 3 implements (4) separately for each time period. The effect of electricity intensity on the productivity-price tradeoff is less precisely estimated when we split the sample, but a bigger cost share for electricity leads to a stronger tradeoff in all four periods.

Figure 4 shows results of the implementation of (4) with estimated elasticities from the instrumental variables estimation of (3) for all four time periods, and Figure 5 shows analogous plots individually for each time period. Both of these figures provide further support for the hypothesis that the tradeoff between electricity physical efficiency and price is stronger for more electricity intensive industries.

6. Competition Effects on Productivity and Price Dispersion

The results thus far show tremendous intra-industry dispersion in electricity price and physical productivity plus evidence of an important tradeoff between the two in the cross section of plants. The evidence further shows that this tradeoff strengthens as electricity's cost share rises. As we discussed above, one explanation for the impact of cost share on the price-productivity tradeoff involves the role of market selection pressures. We now exploit another implication of market selection to formulate and test additional hypotheses.

Other things equal, market selection pressures operate with greater force when product market competition is more intense. In particular, greater competitive intensity truncates the lower tail of the plant-level efficiency distribution. To translate this implication into a testable hypothesis, we follow Syverson (2004a) and exploit the fact that some manufacturing goods are produced and sold primarily in local markets. For local goods, an increase in the number of producers who sell the same good in the same

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local market means an increase in competitive intensity. Thus, we hypothesize that (a) the dispersion of electricity productivity, physical efficiency and price declines with the number of local producers in the industry for local goods, and (b) it is unaffected for national goods.

To test these hypotheses, we use a difference-in-difference approach. Since dispersion within any given industry may reflect many factors, we abstract from unobserved factors by exploiting differences in the local vs. national nature of the goods produced by each industry. That is, some goods (e.g., ready-mixed concrete) are produced primarily for local use while other goods (e.g., roasted coffee) are produced for a national market. From data collected from the 1977 Commodity Transport Survey, we have estimates by industry of the distances that goods are shipped.[11] For this exercise, we designate industries as local if more than 60 percent of the shipments for the industry are shipped less than 100 miles. Using this local/non-local distinction, we estimate regressions of the absolute value of the deviation of plant-level prices and physical efficiency on an indicator variable for the number of local competitors the establishment has in the local market interacted with the local/non-local measure while controlling separately for the local nature of the industry and the density of the local market. For the latter, we use Bureau of Economic Analysis (BEA) component economic areas (CEAs) to define the local market.[12] Given substantial variation across industries in the number of local competitors, we construct a simple dummy variable for local market density

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[11] Chad Syverson provided us with these industry estimates. He discusses the compilation of these estimates from the publicly available 1977 Commodity Transport Survey data in Syverson (2004b).
[12] There are 348 CEAs in the U.S. The CEAs are mutually exclusive and cover the entire U.S. See the BEA Internet site (http://www.bea.gov) for more information on CEAs.

indicating whether the local market has only one plant or two or more competitors.[13]

This *DENS* variable should matter for dispersion only for locally produced goods, and we exploit this in our difference-in-difference specification.

Our specification consists of two stages. In the first stage, we estimate a plant-level regression of log electricity productivity on a fully interacted set of industry and year effects. Additionally, we examine electricity physical efficiency and prices using this specification. It is important to control for industry effects, particularly when examining physical efficiency dispersion, given the inherent differences in measures of output across industries. As both a point of comparison and as an interesting exercise on its own, we also consider a specification where the first stage regression is plant-level log labor productivity regressed on a fully interacted set of industry and year effects.

In the second stage, we estimate difference-in-difference specifications for electricity productivity, electricity price, electricity physical efficiency and labor productivity. These specifications pool plants across Census of Manufactures (CM) years and are of the following form:

$$abs(residual_{et}) = \alpha + \beta LOCAL_{et} + \gamma DENS_{et} + \delta\left(LOCAL_{et} * DENS_{et}\right) + \varepsilon_{et}, \qquad (5)$$

where $LOCAL_{et}$ is an indicator variable for the plant that is equal to 1 if the plant is in an industry where more than 60 percent of the goods are shipped less than 100 miles and $DENS_{et}$ is an indicator variable for the plant that is equal to 1 if the plant is in a local CEA with 2 or more plants producing in the same industry. The dependent variable in (5) is the absolute value of the residual from the first stage regression. The primary

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[13] We construct this variable using the Census of Manufactures (CM) and for CM years only (1963 and years ending in '2' or '7') so that we have the universe of plants. For this reason, the regressions that follow pool only over CM years.

coefficient of interest is δ and the prediction is that $\delta < 0$ if productivity dispersion

declines with the number of producers in the industry in the local market.

Table 4 contains the regression results from our difference-in-difference

regressions. Again, we focus on value added weighting as the most relevant weighting

scheme since the market selection effects should operate on the basis of the most efficient

producers of output. There is a statistically significant and large-in-magnitude negative

coefficient on the interaction term for both electricity productivity and electricity physical

efficiency. These negative coefficients indicate that plants producing local goods in

markets with two or more competing plants have less dispersion in electricity

productivity and physical efficiency. For example, looking at column (3) of Table 4, we

find that for locally produced goods, a denser local market yields a reduction in physical

efficiency dispersion of almost 7 log points. The latter is a large change relative to the

average dispersion (measured by the absolute value) of about 68 log points. Thus, market

density increases to two plants or more in the local market yields almost a ten percent

reduction in dispersion.

While electricity productivity and electricity physical efficiency show significant

effects on dispersion from denser local markets, electricity price does not. The

interaction coefficient for electricity price is small in magnitude and is not statistically

significant.

For comparison, column (4) of Table 4 presents difference-in-difference

regression results for labor productivity. The coefficient on the interaction term is

negative and statistically significant. Interestingly, the finding for labor productivity is

that a denser local market for locally traded goods reduces labor productivity dispersion by about 10 percent.

7. Conclusions

Even within narrow industries and product classes, establishments in U.S. manufacturing exhibit substantial dispersion in electricity productivity and each of its components, physical efficiency and price "efficiency". The dispersion in electricity physical efficiency is larger in magnitude than the comparable dispersion in labor productivity that has been emphasized in the literature.

The substantial observed dispersion in electricity physical efficiency and prices raise the question: how is it that plants seemingly competing in the same market can exhibit such large dispersion in physical efficiency and price efficiency? We explore two possible answers to this question. First, we show that there is a positive tradeoff within industries between the price and physical efficiency of electricity. That is, high price electricity plants tend to be high physical efficiency plants. Not surprisingly, this tradeoff is more pronounced in electricity intensive industries.

Another answer we explore is that plants producing in the same industry (or producing the same product) may not, in fact, be competing in the same market especially if the good is primarily locally traded. That is, plants producing locally traded goods are primarily competing with other plants in that same industry in that local market. To explore the impact of market structure, we build on Syverson (2004a, 2004b) to investigate the impact of market density for locally produced goods on physical efficiency and price dispersion. Using a difference-in-difference specification, we find

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evidence that an increase in local market density for locally traded goods yields a

reduction in the dispersion of electricity productivity and physical efficiency.

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Table 1. Plant-Level Dispersion in Electricity Productivity, Physical Efficiency, Prices, and Labor Productivity

Statistics for log deviations about industry-year or product-year means	Primary Analysis Sample				Homogeneous Products Sample			
	Electricity Productivity	Physical Efficiency	Price per kWh	Labor Productivity	Electricity Productivity	Physical Efficiency	Price per kWh	Labor Productivity
Sample Weighted								
Mean of Absolute Value	0.63	0.68	0.28	0.47	0.62	0.68	0.28	0.48
Standard Deviation	0.87	0.92	0.38	0.66	0.85	0.91	0.38	0.69
90-10 Dispersion	1.96	2.13	0.86	1.44	1.94	2.12	0.87	1.44
90-50 Dispersion	0.95	1.05	0.45	0.72	0.95	1.05	0.45	0.70
50-10 Dispersion	1.01	1.08	0.42	0.71	0.99	1.07	0.42	0.74
Value Added Weighted								
Mean of Absolute Value	0.62	0.64	0.25	0.53	0.75	0.80	0.27	0.47
Standard Deviation	0.87	0.90	0.32	0.71	1.08	1.15	0.35	0.61
90-10 Dispersion	1.90	1.97	0.78	1.66	2.26	2.32	0.86	1.46
90-50 Dispersion	0.97	1.01	0.40	0.86	1.30	1.36	0.45	0.79
50-10 Dispersion	0.93	0.96	0.38	0.81	0.96	0.96	0.41	0.67
Purchase Weighted[*]								
Mean of Absolute Value	0.60	0.62	0.25	0.46	0.58	0.56	0.26	0.42
Standard Deviation	0.82	0.85	0.33	0.67	0.79	0.78	0.34	0.60
90-10 Dispersion	1.84	1.92	0.76	1.41	1.82	1.72	0.85	1.30
90-50 Dispersion	0.92	0.96	0.40	0.67	0.91	0.92	0.43	0.61
50-10 Dispersion	0.92	0.96	0.36	0.74	0.91	0.80	0.42	0.69

[*] Labor productivity statistics are hours weighted rather than purchase weighted.

Source: Authors' calculations on the PQEM database for pooled years 1963, 1967, and 1972-2000.

Notes: The Primary Analysis Sample excludes industries styled as "miscellaneous" and "not elsewhere classified." See text Section 2.1 for other sample restrictions. The Homogeneous Products Sample is limited to plants in the following product categories: corrugated and solid fiber boxes, hardwood plywood, ice, motor gasoline, ready-mixed concrete, roasted coffee, and white-pan bread. Statistics are for log deviations around four-digit industry or product means. All statistics make use of sample weights in addition to any other weighting that is indicated.

Table 2. Plant-Level Dispersion around Product-Year Means by Product Category

Product Category	Mean Absolute Value of Log Deviations				Standard Deviation of Log Deviations			
	Electricity Productivity	Physical Efficiency	Price per kWh	Labor Productivity	Electricity Productivity	Physical Efficiency	Price per kWh	Labor Productivity
Boxes	0.51	0.57	0.26	0.33	0.68	0.75	0.33	0.45
Hardwood Plywood	0.44	0.46	0.27	0.38	0.59	0.61	0.35	0.48
Ice	0.75	0.74	0.25	0.46	1.05	1.03	0.33	0.64
Motor Gasoline	0.77	0.80	0.27	0.49	1.13	1.20	0.36	0.64
Ready-Mixed Concrete	0.65	0.72	0.28	0.53	0.88	0.96	0.36	0.76
Roasted Coffee	0.89	0.78	0.67	0.94	1.09	1.02	0.93	1.14
White-Pan Bread	0.45	0.48	0.24	0.39	0.60	0.63	0.31	0.54

Source: Authors' calculations on the PQEM database for pooled years 1963, 1967, and 1972-2000.

Note: Statistics computed on a sample-weighted basis.

Table 3. The Plant-Level Empirical Relationship between Physical Efficiency and Price

Plant-Level Regression Specification: $\tilde{\gamma}_{ei} = \beta_i\,\tilde{p}_{ei} + \varepsilon_{ei}$, where $\tilde{\gamma}$ and $\tilde{p}$ are log value added per kWh and log price per kWh deviated about their respective industry-year means.

Summary of Results for Industry-Level β Estimates

A. Least Squares Estimation	Time Period			
	1963-1973	1974-1978	1979-1984	1985-2000
Percent Positive	98.9	98.1	96.8	98.0
Percent Positive & Statistically Significant	93.5	91.4	90.4	92.7
Percent Negative & Statistically Significant	0.5	0.0	1.1	0.6
Number of Industries	372	374	374	504
Simple Mean of β Estimate	0.98	0.83	0.85	0.87
Value Added Weighted Mean of β Estimate	0.85	0.74	0.74	0.62
B. Instrumental Variables Estimation (Industries with first-stage $R^2 > 0.20$.)	Time Period			
	1963-1973	1974-1978	1979-1984	1985-2000
Percent Positive	86.1	79.5	90.5	89.6
Percent Positive & Statistically Significant	57.0	48.7	59.5	79.1
Percent Negative & Statistically Significant	2.5	5.1	3.7	3.1
Number of Industries	79	39	190	483
Simple Mean of β Estimate	0.70	0.56	0.67	0.74
Value Added Weighted Mean of β Estimate	0.51	0.47	0.59	0.48
C. Least Squares Estimation (Same set of industries as in panel B.)	Time Period			
	1963-1973	1974-1978	1979-1984	1985-2000
Percent Positive	97.5	97.4	97.4	98.1
Percent Positive & Statistically Significant	88.6	71.8	90.0	93.0
Percent Negative & Statistically Significant	1.3	0.0	1.1	0.6
Number of Industries	79	39	190	483
Simple Mean of β Estimate	0.99	0.78	0.81	0.86
Value Added Weighted Mean of β Estimate	0.67	1.00	0.72	0.61

Notes: We estimate the regressions by industry for each time period using our Primary Analysis Sample. We drop industries with fewer than 20 plant-level observations during the time period. Panels A and B report results for weighted LS and weighted IV estimation, respectively, with weighting by value added (and sample weights). The instrument in Panel B is the plant's predicted log price in a cross-sectional regression on roughly 3,000 county fixed effects. Panels B and C report LS and IV results for a reduced set of industries for which the first-stage regression R-squared value exceeds 0.20. Statistical significance is at the 5 percent level. Shipments weights and equal weights yield highly similar results.

Table 4. Local Market Competition Effects on Dispersion in Productivity and Prices

Dependent Variable: absolute value of the residual in a regression of the (log) indicated variable on a fully interacted set of year and industry effects.

	Electricity Productivity	Electricity Price	Electricity Physical Productivity	Labor Productivity
	(1)	(2)	(3)	(4)
Intercept	0.595	0.251	0.616	0.490
	(0.002)	(0.001)	(0.002)	(0.001)
LOCAL	-0.043	0.004	-0.031	0.029
	(0.008)	(0.003)	(0.008)	(0.006)
DENS	0.027	0.001	0.030	0.024
	(0.002)	(0.001)	(0.002)	(0.002)
*LOCAL*DENS*	-0.056	0.001	-0.067	-0.046
	(0.009)	(0.003)	(0.009)	(0.006)
Adjusted R^2	0.002	0.000	0.002	0.001
N	394,362	394,362	394,362	394,362

Source: Authors' calculations on the PQEM database for pooled CM years: 1963, 1967, 1972, 1977, 1982, 1987, 1992, and 1997.

Note: All four regressions are estimated by weighted least squares with weighting by value added (and sample weights).
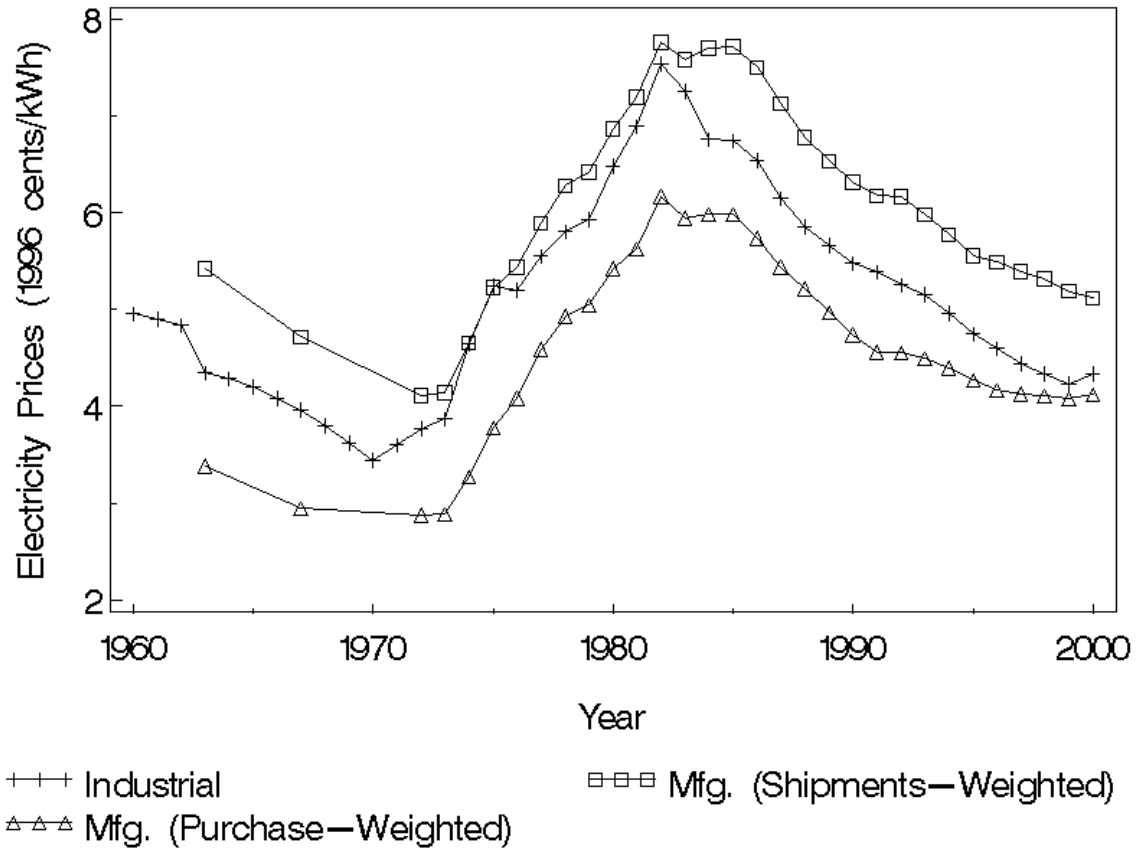
Source: Energy Information Administration for the Industrial series; authors'
calculations on PQEM data for Manufacturing.

Note: Nominal values deflated by the GDP implicit price deflator.

Figure 1. Real Electricity Prices, Industrial and Manufacturing Customers, 1960-2000
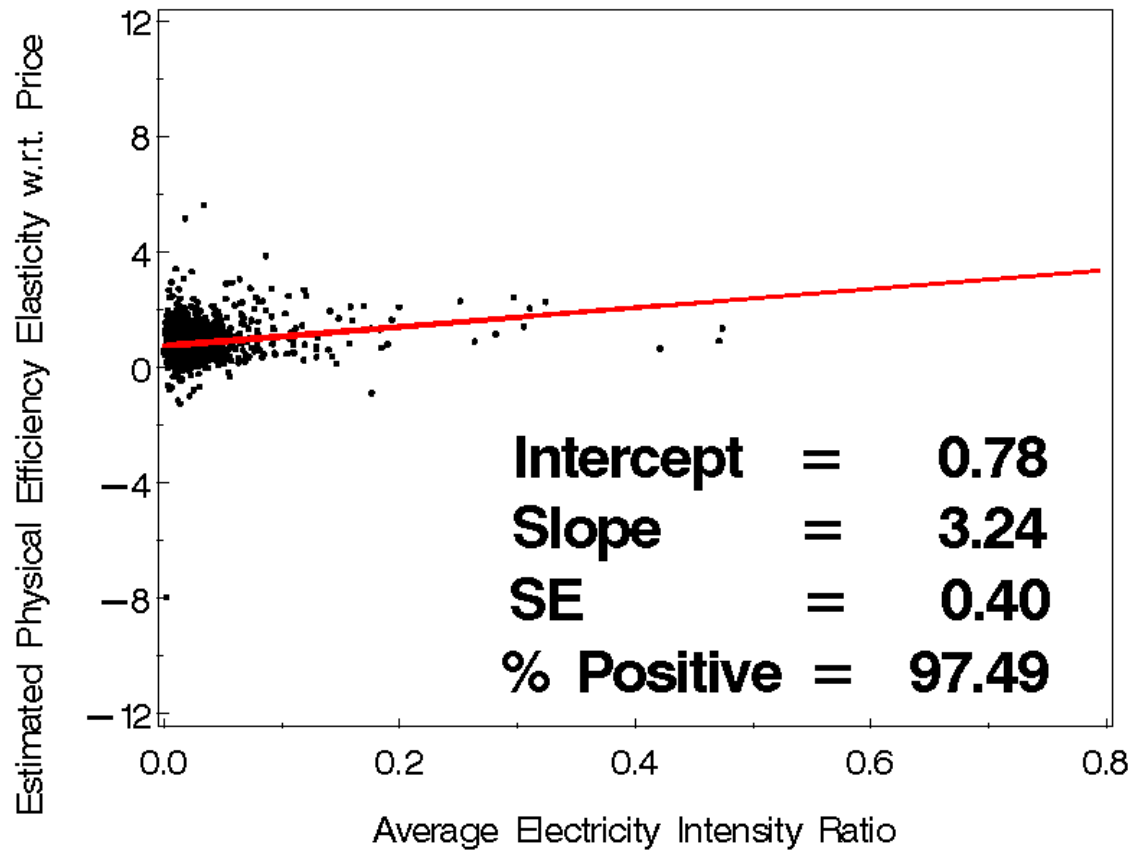
Source: Authors' calculations on PQEM data.

Notes: The elasticity is estimated by weighted least squares as described in the text and Table 3. The electricity intensity ratio is the time-averaged value for electricity expenditures as a fraction of industry value added. Each point in the figure corresponds to a single four-digit industry in one of the four time periods, 1963-1973, 1974-1978, 1979-1984 and 1985-2000. The plotted regression line is fit by OLS to the industry-level data.
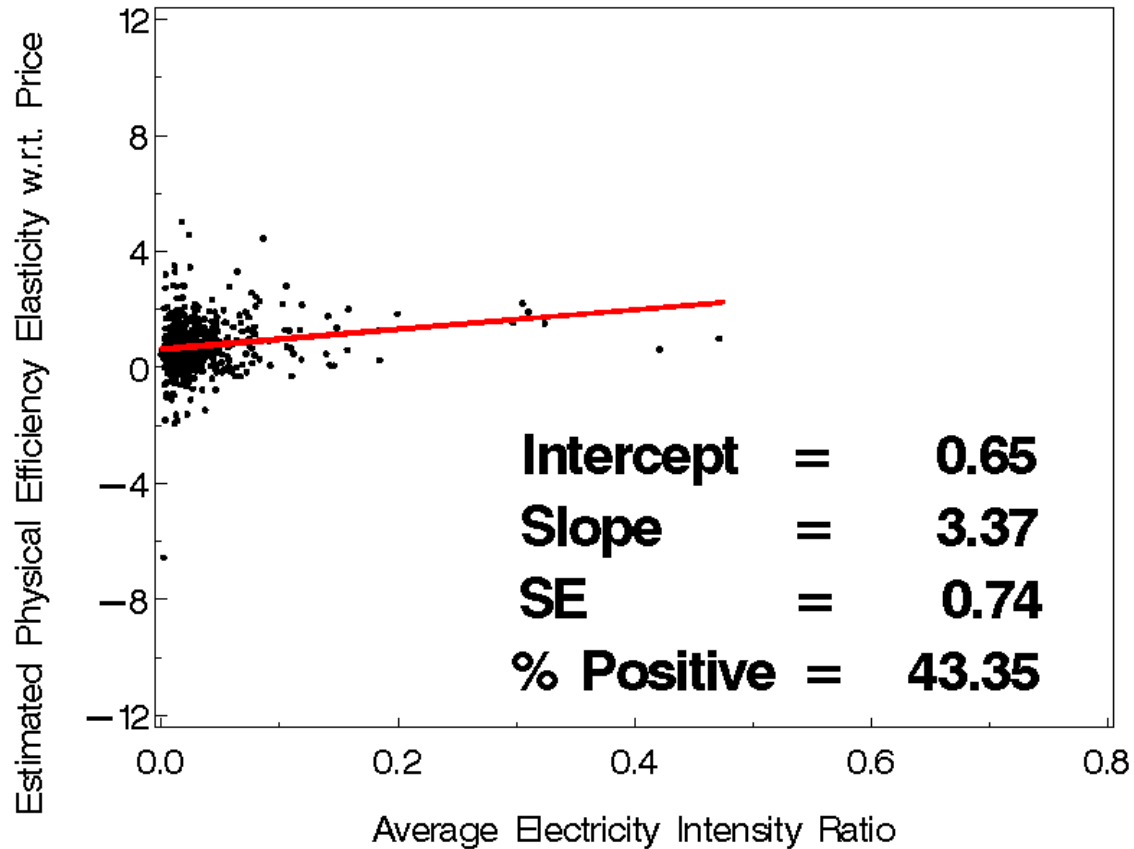
Figure 2. The Effect of Electricity Intensity on the Price-Productivity Tradeoff
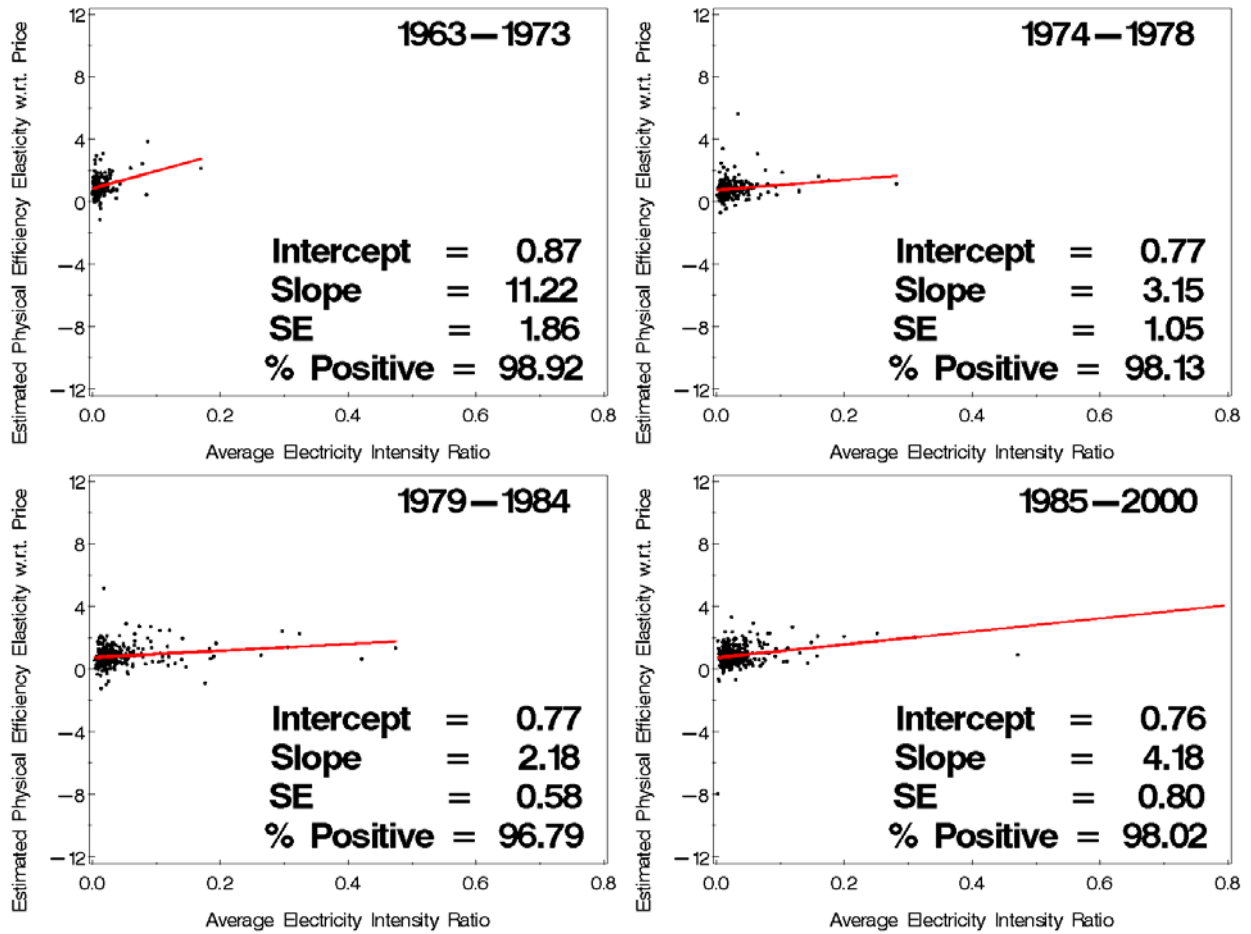
Source: Authors' calculations on PQEM data.

Notes: The elasticity is estimated by weighted least squares as described in the text and Table 3. The electricity intensity ratio is the time-averaged value of electricity expenditures as a fraction of industry value added. Each point in the figures corresponds to a single four-digit industry in the indicated time period. The plotted regression lines are fit by OLS to the industry-level data.
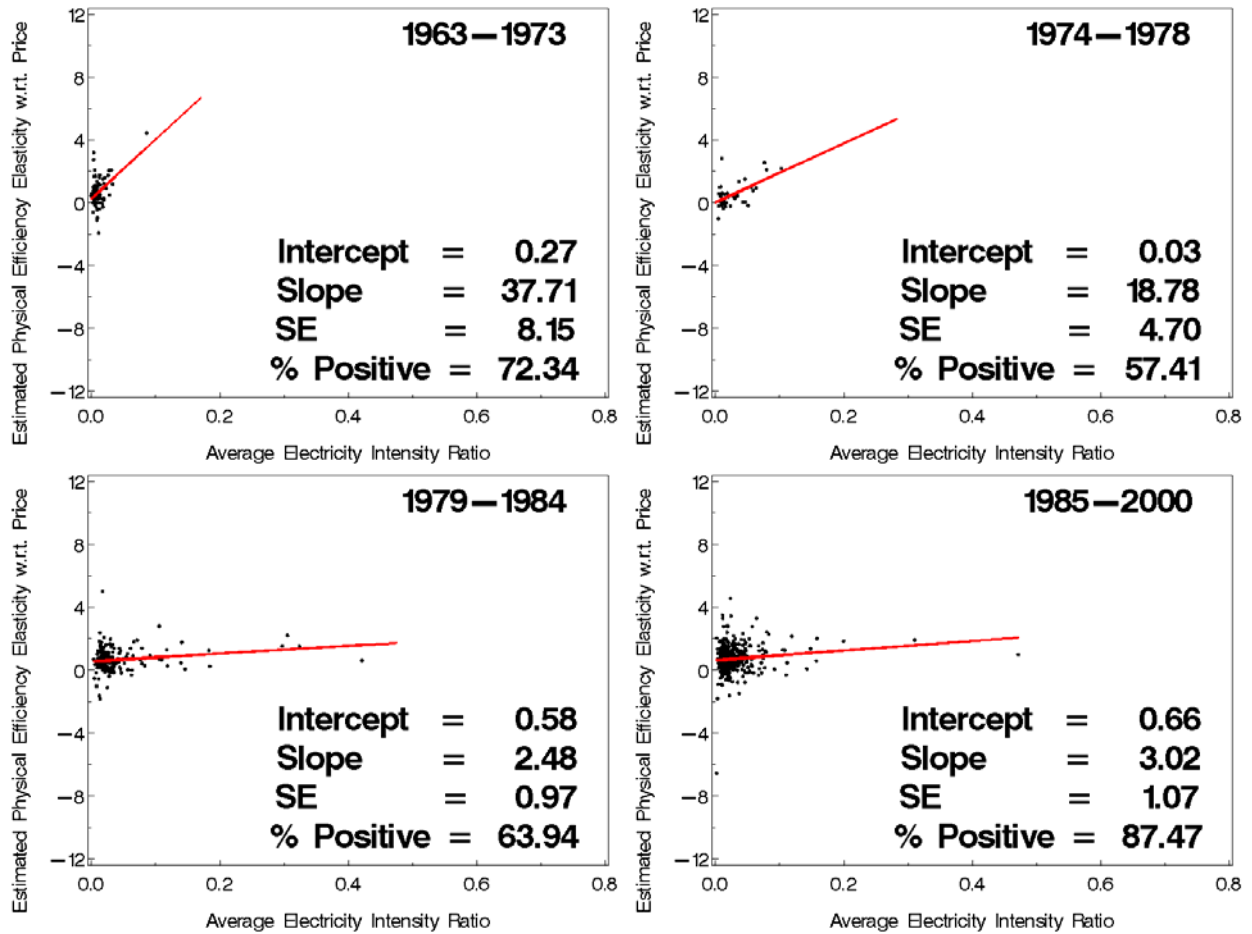
Figure 3. The Effect of Electricity Intensity on the Price-Productivity Tradeoff by Time Period

Source: Authors' calculations on PQEM data.

Notes: The elasticity is estimated by instrumental variables regression as described in the text and Table 3. The electricity intensity ratio is the time-averaged value for electricity expenditures as a fraction of industry value added. Each point in the figure corresponds to a single four-digit industry in one of the four time periods, 1963-1973, 1974-1978, 1979-1984 and 1985-2000. The plotted regression line is fit by OLS to the industry-level data.

Figure 4. The Effect of Electricity Intensity on the Price-Productivity Tradeoff, Instrumental Variables Specification

Source: Authors' calculations on PQEM data.

Notes: The elasticity is estimated by instrumental variables regression as described in the text and Table 3. The electricity intensity ratio is the time-averaged value of electricity expenditures as a fraction of industry value added. Each point in the figures corresponds to a single four-digit industry in the indicated time period. The plotted regression lines are fit by OLS to the industry-level data.

Figure 5. The Effect of Electricity Intensity on the Price-Productivity Tradeoff by Time Period, Instrumental Variables Specification